Route Optimization for Spatially Localized Delivery Routes

Jeremiah Clemens-Dannecker
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Introduction

Throughout my time at the University of Wisconsin–Eau Claire, I have been working at a beverage distribution company called Lee Beverage of Wisconsin, LLC. Lee Beverage specializes in daily deliveries for hundreds of beverage products. With warehouse locations in Eau Claire, Oshkosh, and Rothschild, the company serves thirty-three counties across the state of Wisconsin. The Eau Claire facility, where I am based, manages spatially localized routes, typically limited to two or three counties.

My goal with this project was to answer the question: "Will route optimization improve the efficiency of already spatially localized delivery routes?" In an industry where every mile driven adds cost, reducing vehicle time on the road presents a key opportunity for operational improvement. By applying geospatial analysis techniques, my aim was to identify routing inefficiencies within a localized company.

This paper begins with a review of literature on current route optimization and the use of GIS in transportation. I then explain the methods used to analyze and optimize current routes using real-world data provided by Lee Beverage. These findings shed light on how geospatial analysis can help save costs and improve delivery logistics—not just for Lee Beverage, but for other companies with similar operations. By pinpointing where current routes fall short, this research offers practical strategies that could be applied across many industries that rely on local distribution networks.

Literature Review

Optimization of delivery has been a major focus in logistics, transportation, and GIS for decades. The Traveling Salesman Problem (TSP) is one of the most recognizable route optimization techniques due to its simplicity and efficiency. It has been one of the most studied problems in combinatorial optimization, providing a solid theoretical framework for efficient route planning (Lawler et al. 1985).

Recent studies have explored a variety of metaheuristic methods to effectively solve optimization problems. A study conducted in 2022 examined methods including genetic algorithms, ant colony optimization, and the multiple TSP to demonstrate that heuristic-based methods can achieve near-optimal solutions within a reasonable computational timeframe (Dhanalakshmi, Parthiban, and Anbuchezhian 2022). Similarly, Gupta, Gupta, and Aggarwal

(2024) conducted a comparative study emphasizing the importance of selecting methods that balance solution quality with computational efficiency for effective route planning.

From a methodological perspective, heuristic infrastructure tools in R, such as the TSP package developed by Hahsler and Hornik (2007), provide a user-friendly platform for applying TSP heuristics to route optimization problems. Their paper offers guidelines on methods, algorithms, and example scripts to enhance the user's experience with the software. Delivery route optimization can also be applied practically to small-scale distribution networks, as demonstrated by a 2021 senior design project. This study exemplifies how integrating route optimization techniques with real-world constraints can lead to significant operational efficiencies and cost savings.

Analysis & Findings

Intro

The current delivery routes assigned to Lee Beverage drivers are spatially localized, meaning they are geographically constrained to a service area, typically covering two to three counties or cities. It is reasonable to assume that some form of route planning is already incorporated into these routes, whether through experience-based knowledge or digital mapping tools. However, there remains potential for further refinement. With the use of Geographic Information Systems (GIS), companies like Lee Beverage can develop repeatable, scalable, and internal route optimization workflows to improve overall distribution control and enhance long-term operational flexibility (Golden, Raghavan, and Wasil 2008).

Although the current routes are already structured to reduce time spent on the road for delivery drivers, route optimization methods can further improve the efficiency of these truck routes. Factors such as vehicle time on the road, total distance driven, and fuel consumption significantly impact Lee Beverage's overall operational costs. Improving these efficiency metrics contributes directly to increasing company profitability (Dhanalakshmi, Parthiban, and Anbuchezhian 2022; Gupta, Gupta, and Aggarwal 2024).

The area of study (Figure 1) for this project encompasses the service area of counties that Lee Beverage of Wisconsin covers. The company's territory includes 33 counties across the state of Wisconsin.

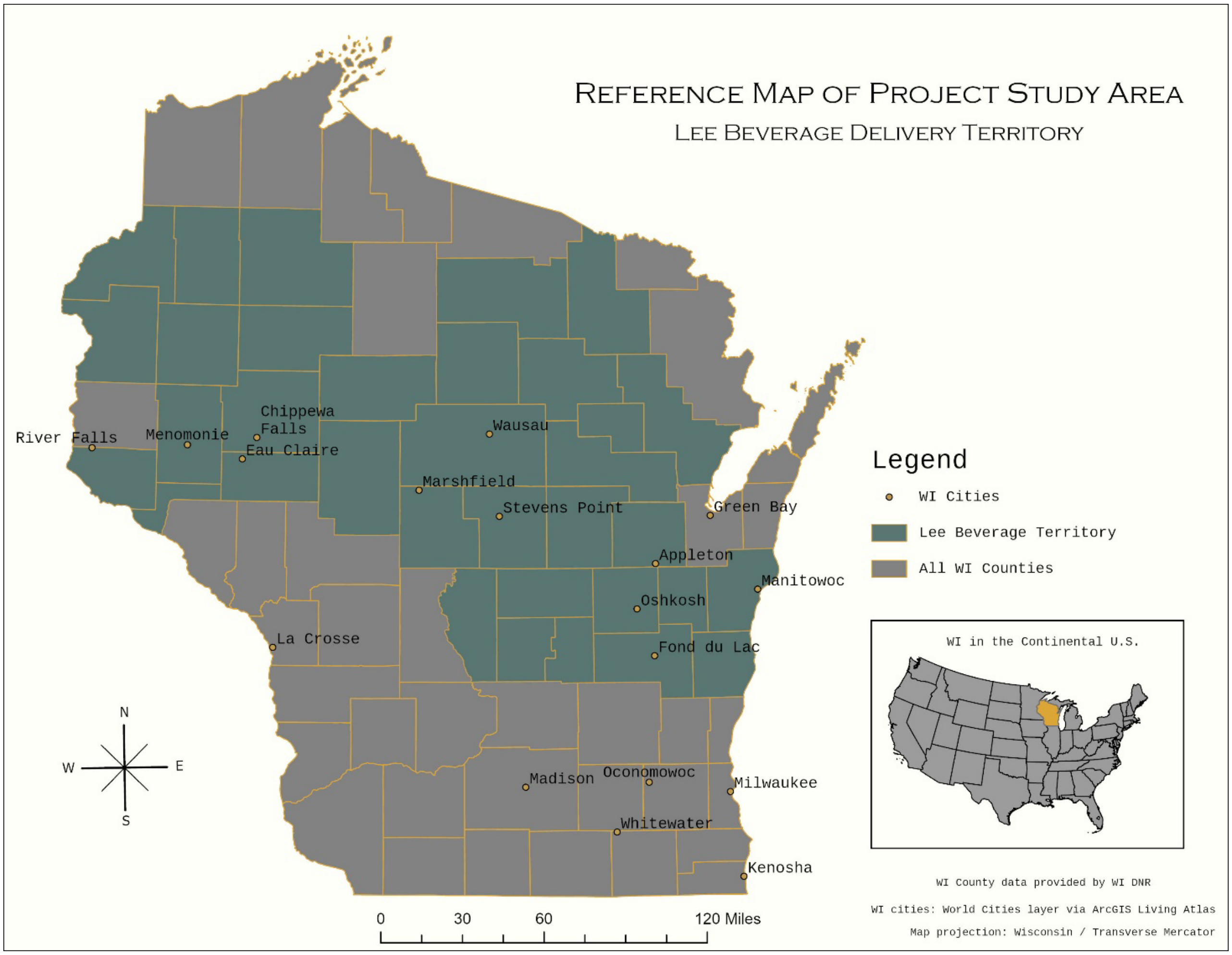

Figure 1

Methodology

Choosing an Approach

Lee Beverage of Wisconsin provided me with six real side-load truck delivery routes. Each route was organized by Truck ID: Sierra Nevada, Coors, White Claw, PBR, Smirnoff, and Alaskan. The data included stop numbers and addresses in [Street, City, State, Zip code] format. I compiled each route into Microsoft Excel, added the Lee Beverage warehouse location, and exported the document as a CSV file for further analysis.

When deciding on a method for route optimization, I considered several options before choosing to write a function in R. While ArcGIS Pro's GUI offers route analysis tools, it lacked the automation and replicability needed for this project. Manual repetition for every stop change, road closure, or address update was not practical. I also explored Python and ArcGIS Pro notebooks, which provided access to tools like ArcPy and Esri's API. However, limitations in automation—such as the inability to trigger credit estimation for geoprocessing tools—proved too restrictive for my workflow.

Ultimately, R offered a more streamlined solution. Its variety of spatial analysis and data manipulation packages made it well-suited for geocoding, route optimization, and efficiency calculations, providing the flexibility and repeatability needed for this project.

Explanation of Script

The function I created reads a CSV file of delivery addresses and geocodes them using the Google Maps API. The code then checks for mismatched or invalid addresses. If no errors are found, the geocoded addresses are stored in a new data frame, sorted by Truck ID. Next, the function assigns a warehouse point to the data frame. This step is essential, as each route needs to start and end at the warehouse to ensure the route is complete.

Once the warehouse point is combined with the delivery stops, a distance matrix is initialized for each truck. This matrix calculates the distance from stop to stop by calling the OpenRouteService (ORS) API, which retrieves network-based driving distances rather than relying on simple straight-line (Euclidean) measurements (OpenRouteService 2024). This forms the core of the Traveling Salesperson Problem (TSP) solution.

After the distance matrix is populated, the TSP package in R solves the route using the "nearest insertion" method, which adds the nearest point to the current route at each step (Hahsler and Hornik 2007).

When the TSP is solved, the function produces multiple outputs:

- A data frame containing the optimized stop sequence.
- A point shapefile saved in a designated output folder for further analysis or visualization in other GIS software.
- A route visualization generated using ggplot2 to display the optimized path within R.

After generating the optimized routes, I used an additional script to compare the optimized route data frames with the original route data. This script calculated the total driving distance in miles and total driving time in minutes for both scenarios, allowing for a direct analysis of efficiency improvements. Additionally, I estimated the total fuel savings or additional costs based on a baseline gasoline price of $2.945 per gallon, reflecting the average price in Wisconsin as of May 2025 (U.S. Energy Information Administration 2025).

I also chose to further visualize the newly optimized routes in **ArcGIS Pro** to produce high-quality static maps. This decision was based on my familiarity with ArcGIS Pro's cartographic capabilities and to demonstrate that the function's outputs are cross-platform, allowing for seamless integration between R-based analysis and traditional GIS software (Esri 2024).

Analysis

Sierra Nevada Truck

Route optimization for the Sierra Nevada truck (Figure 2) yielded the most significant results of my analysis. Compared to the current Sierra Nevada route, the optimized path reduced the total distance traveled by 56.28 miles, cut driving time by 83.9 minutes, and resulted in estimated fuel savings of $25.61. For this route, the application of the Traveling Salesperson Problem (TSP) using the nearest insertion method proved highly effective in improving these efficiency metrics compared to the existing route (Hahsler and Hornik 2007).

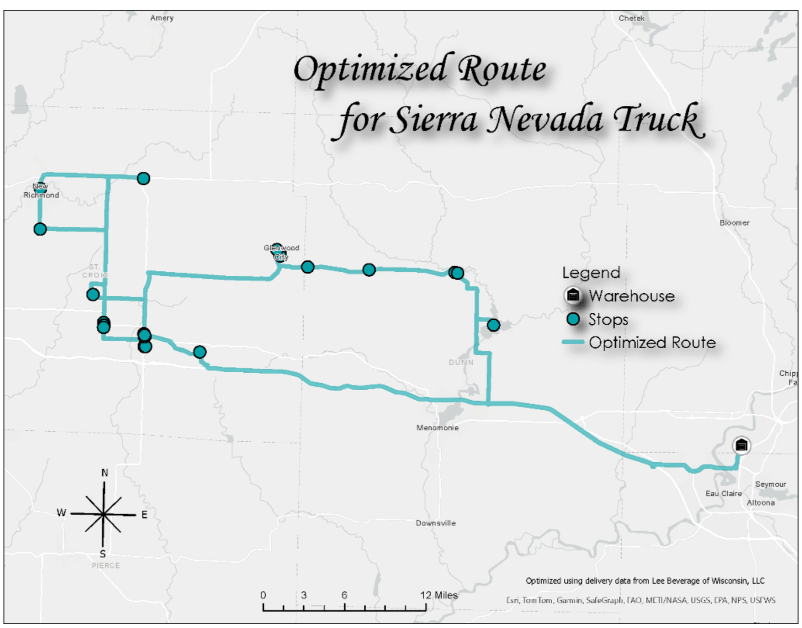

Figure 2

Coors Truck

More positive results came from the Coors delivery route (Figure 3). The optimized route saved 18.2 miles, reduced driving time by 22.9 minutes, and resulted in fuel savings of $8.28. Although these results were not as significant as those from the Sierra Nevada route, they still represent meaningful improvements in efficiency.

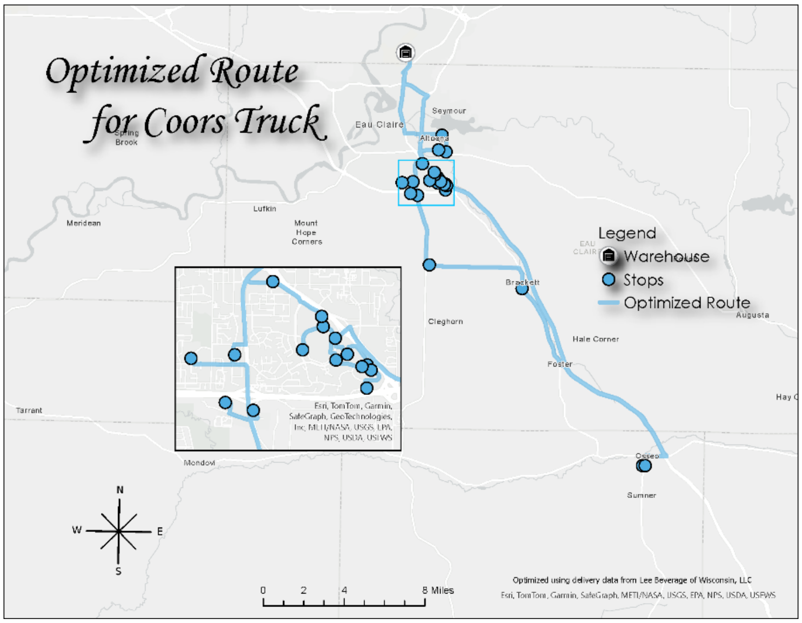

Figure 3

White Claw Truck

Optimization for the White Claw delivery route (Figure 4) did result in improvements, but not by much. The optimized route saved 0.6 miles, reduced driving time by 3.1 minutes, and saved $0.27 in fuel costs. While these improvements may seem small, it is important to consider that this reflects just a single day of deliveries. When these savings are accumulated over multiple weeks, the overall efficiency gains become more significant.

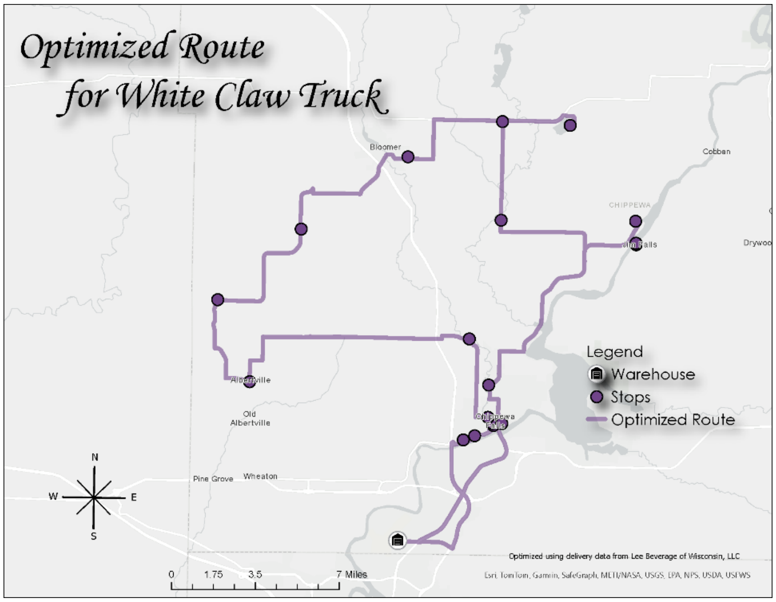

Figure 4

PBR Truck

The PBR truck (Figure 5) was the last route that benefitted from the optimization process. The optimized route saved 14.76 miles, reduced driving time by 18.7 minutes, and resulted in fuel savings of $6.72 compared to the current route. In terms of efficiency, this route was back on par with the optimized Coors and Sierra Nevada routes.

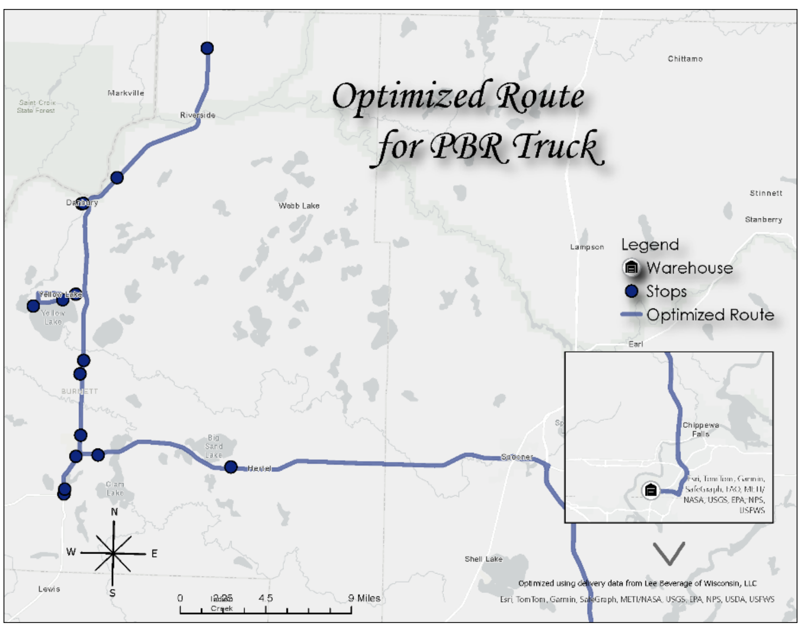

Figure 5

Smirnoff Truck

The Smirnoff truck (Figure 6) was the first of the six routes to regress as a result of the optimization process. Compared to the current route, the optimized Smirnoff route added 11.81 miles and 8.6 minutes of travel time. This resulted in an increase of $5.37 in fuel costs.

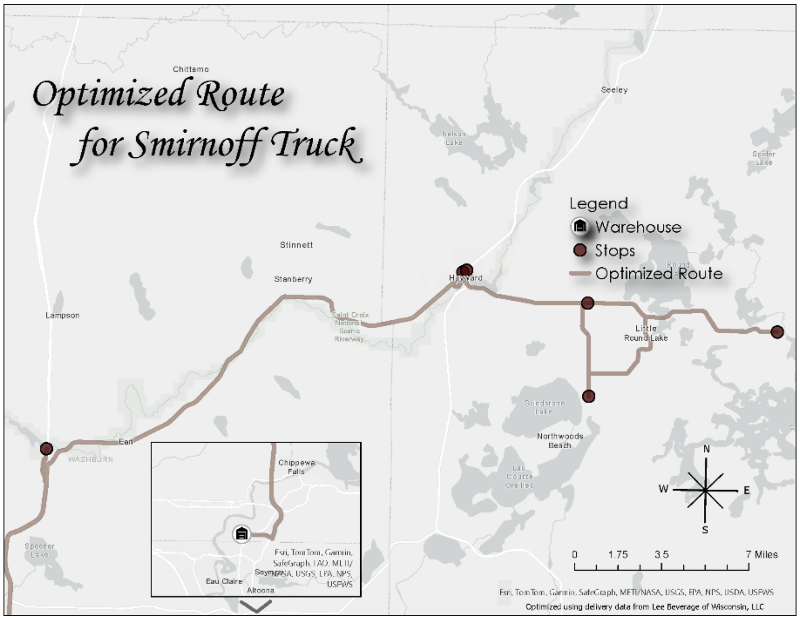

Figure 6

Alaskan Truck

The Alaskan truck route (Figure 7) experienced by far the worst outcome from the optimization process. The optimized route added 56.62 miles, 134.6 minutes of travel time, and resulted in an increase of $25.61 in fuel costs, nearly offsetting the savings achieved by the Sierra Nevada truck route. This route experienced a clear regression, not optimization.

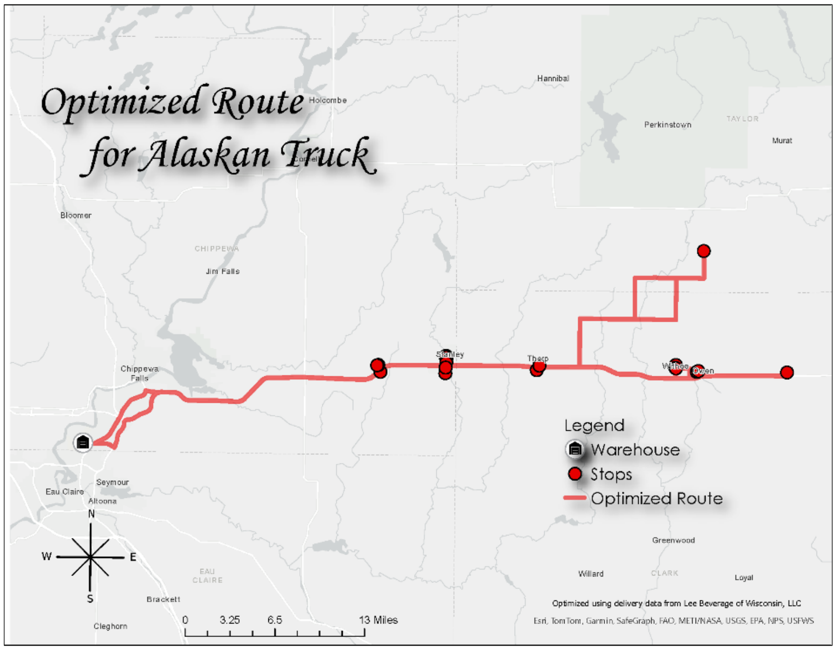

Figure 7

Discussion

Limitations & Drawbacks

The efficiency measurements and the route optimization impact chart (Figure 8) show that the TSP-based route optimization function benefitted some routes but also hindered others. There are several reasons why route optimization results can vary across different routes. One key factor is the distribution of stops—whether they are scattered, clustered, or arranged linearly—which significantly impacts the effectiveness of optimization (Golden, Raghavan, and Wasil 2008). Additionally, TSP complexity increases with the number of stops; routes with fewer stops may already be near-optimal, leaving little room for improvement (Lawler et al. 1985). Another important consideration is the location of the depot relative to the stops. A warehouse located on the periphery of a route can result in longer and more awkward loops during optimization (Esri 2024).

Solutions

To enhance this project, I would consider experimenting with alternative optimization techniques. One option would be to explore the Vehicle Routing Problem (VRP) framework, which accounts for multiple vehicles and additional constraints. I would also experiment with different TSP heuristics and algorithms, such as Lin-Kernighan or simulated annealing, to potentially improve optimization results. Incorporating time-of-day factors and real-world network constraints could further refine the analysis and produce more practical routing solutions.

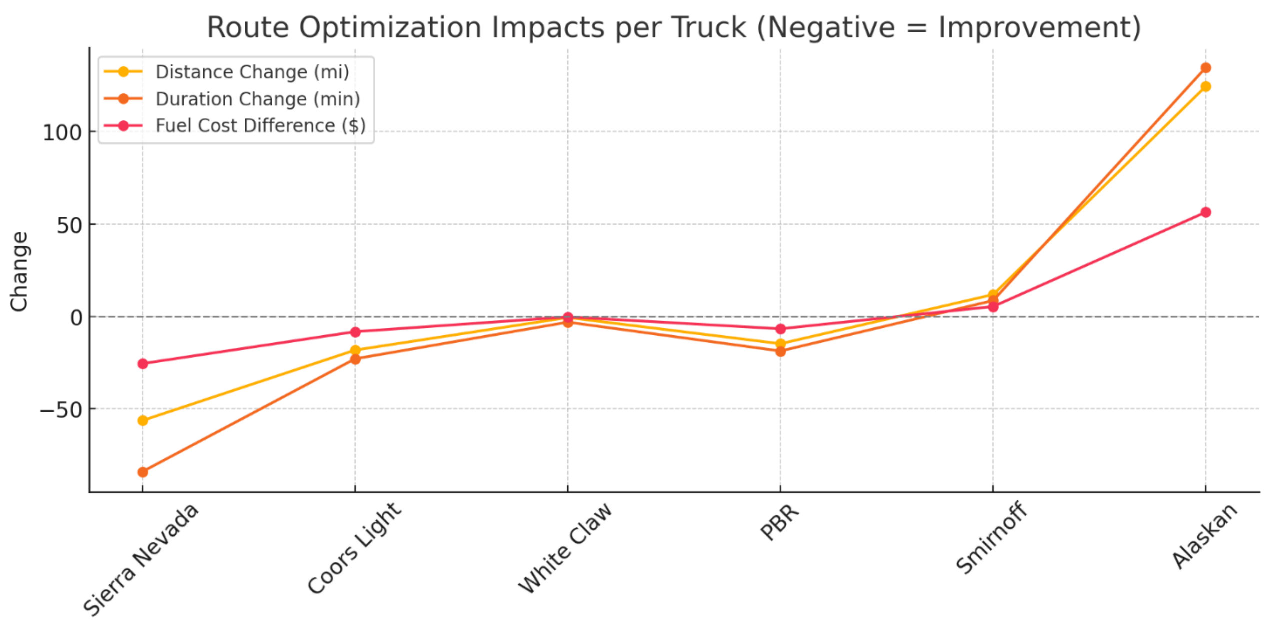

Figure 8

Conclusions

This project set out to answer a simple but important question: does route optimization improve the efficiency of delivery routes that are already spatially localized? Based on the results, the answer is yes — but not always. Out of the six routes I analyzed, four showed clear improvements in travel distance, time spent on the road, and fuel costs. While this is a small sample compared to the number of routes Lee Beverage runs daily, even small savings can add up to significant cost reductions when considered over a larger span of time.

At the same time, two routes became less efficient after optimization. This shows that route optimization is not a one-size-fits-all solution. The layout of the stops, the location of the warehouse, and even the way the original route was designed can all impact whether optimization methods like the Traveling Salesperson Problem (TSP) help or hurt efficiency. In some cases, more advanced methods may be needed to see real improvements.

The significance of this project extends beyond the scope of a single beverage distributor in Wisconsin. Route optimization intersects with concepts such as spatial networks, humanenvironment interactions, and the movement of goods across space. Efficient transportation logistics are critical to urban planning, regional development, and global supply chains. By applying spatial analysis tools and network-based optimization methods, this project demonstrates how geographers may contribute to solving real-world problems through a spatial lens, emphasizing the broader importance of geographic inquiry in an increasingly connected and logistics-driven world.